Digital twin of forged part to reduce distortion in machining

Hugo Chabeauti[a,b,c], Mathieu Ritou (2)[b,*], Bruno Lavisse[a], Guenael Germain[a], Virginie Charbonnier[c]

[a] Arts et Métiers ParisTech, Campus d'Angers, LAMPA, 2 bd du Ronceray, Angers 49035, France
[b] Nantes University, LS2N (Laboratory of Digital Sciences of Nantes, UMR CNRS 6004), 1 Quai de Tourville, Nantes 44000, France
[c] AIRBUS Operations, rue de l'aviation, Bouguenais 44340, France

Keywords:
Digital twin
Residual stress
Deformation

A B S T R A C T

When long parts are machined in forged blanks, the variability of bulk residual stress (RS) fields leads to uncontrolled deformation after machining, requiring manual reshaping. An original hybrid digital twin of forged part is thus proposed to manage the bulk RS variability and reduce part distortion in machining. The behavior model of parts relies both on reduced models of thermomechanical simulations of the forging process variability, on-line measurements and machine learning from the previous parts deformations. Adaptive machining solutions can then be simulated for a rapid decision-making. The approach was validated on a series of aeronautic forged parts.

1. Introduction

Metallic parts for aeronautic structures are usually machined in thick plates, with high material removal rate. More and more, they are also machined in forged blanks, requiring a lower material removal. During the manufacturing of the blank, plastic deformations and thermal gradients generate a residual stress (RS) field, which can be of high intensity and gradient in the part [1,2]. During machining, the RS field of the part is modified by the material removal, which can lead to distortion at the unclamping. The part then deforms to return to a free state, with a balanced RS field [3]. The thermomechanical loads in machining also introduce additional RS at the part surface, on a depth of a few hundred microns, non-negligible for thin parts [4,5]. But for massive parts, the RS induced by the cut is negligible, compared to the amount of bulk RS that is released by material removal [6].

The main issue is the variability of the bulk RS field that can be observed from one part to another, particularly for forged blanks, which leads to uncontrolled part distortion after machining. For long forged parts, a costly manual reshaping is often necessary after machining, so that the part meets its geometrical specifications before the assembly. One solution is to optimize the positioning of the final part in its blank, in order to reduce the distortion after machining [7]. Other solutions also exist [1], e.g. based on error compensation [8] or adaptive clamping [9].

If the blank manufacturing process is repeatable, the best solution can be found empirically, by reinforced learning, or by trial and error approach (without knowing the RS field). If the bulk RS field is known, finite element model (FEM) simulations of the relaxation of the residual stresses can be performed. For rolled plates, the RS field can be known, because the geometry is simple and the thermomechanical gradients are known [2,7]. But few works address more complex part geometries.

On forged blank, the variability of RS field between parts is a critical issue that leads to unrepeatable part deformation. A solution would be to measure the bulk RS field of each part; but non-destructive techniques, such as XRD, can only analyze the part at low depths or cannot be used on a production line. Exploiting a nominal simulation of RS field is inefficient, since it does not reduce the impact of the variability. An accurate identification, for each part, of all key process parameters is unrealistic, which makes impossible an accurate simulation of RS field for each forged blank by physic-based approach.

In-process data is thus required for each part to capture its specific behavior, which leads to digital twin (DT) technologies, relying on a behavior model, to manage the bulk RS variability and deformation. Indeed, the objective of a digital twin is to sense and reflect accurately the behavior and real-time state of an object; to enable analysis, simulation, prediction and optimization [10]. DT can be developed for product, process, machine or production system and should be individualized (for each element), of high-fidelity (of behavior), near real-time (responding with low latency) and controllable (by closed loop).

Approaches can be data-driven, which is efficient for very complex and uncertain process; but physically impossible solution might be proposed by the DT, which can affect their acceptability. For part distortion, Zhao et al. [11] suggested a deep learning model, associated with machinings of many thin layers of the part and deformation measurements. It significantly increases the machining duration and a big dataset with hundreds of parts is necessary to train the model. Also based on thin layer removals in rolled plates, [9] and [12] predict each part deformation with polynomial models, which is compatible with small datasets; and the latter proposed an adaptive control that

* Corresponding author.
E-mail address: mathieu.ritou@ls2n.fr (M. Ritou).

https://doi.org/10.1016/j.cirp.2023.04.021

deforms the part between layers. The approaches rely on the hypothesis that the shape of the bulk RS field is identical between parts and that only the magnitude varies. It seems true for rolled plates, but not for forged parts where the RS field shape can vary [13]. Therefore, a hybrid DT approach, which takes full advantage of data-driven and physic-based approaches, seems necessary to tackle the complex issue of the RS field variability in forged parts. Indeed, without physics, unrealistic RS field shapes could be predicted; and without data and learning, FEM models could not be updated accurately.

In this paper, an original digital twin of forged part is proposed to reduce post-machining distortion. It uses information gained early in the machining process to predict the residual stress state in the part and then corrects the machining process to obtain a favorable outcome; through reduced model of RS field simulations, on-line measurements and machine learning from prior parts deformations. The concept is detailed and then applied in an industrial use-case of long forged part of aeronautic structure.

2. Hybrid digital twin of forged part in machining

The variability of the bulk RS field from one forged blank to another is a key issue in industry, which leads to uncontrolled and unrepeatable part distortion after machining. It cannot be solved by nominal simulation and an adaptative machining is thus suitable for each part. In-process data is necessary to capture the specific behavior of each part. Moreover, this behavior should be identified before or at an early stage of machining; when enough uncut material remains on the blank, to enable an adaptation of the following machining steps.

To tackle this difficult issue, an original digital twin of forged part is proposed to manage the variability of the bulk RS field, in order to reduce the part distortion after machining. The hybrid digital twin relies both on simulations and in-process data (cf. Fig. 1). Indeed, three key elements are necessary to predict the mechanical behavior of a given forged part at an early stage of its machining:

- a reduced model of FEM simulations of the forging process variability (to model realistic RS fields)
- machine learning from the deformations of the previous parts
- the measure of the current part's deformation at an early stage of its machining (to capture its specific behavior)

If one of the three elements is missing, the behavior of the current part cannot be predicted accurately and early. The reduced model of FEM simulations of process variability and the machine learning from previous parts deformation are computed offline. When a new part is produced, its machining is stopped at an early stage to capture the part's early deformation (e.g. after a first rough milling operation and unclamping). The reduced model of bulk RS field then enables fast computations to identify the behavior model of the current part, simulate different adaptive solutions and make a decision rapidly to reduce the part's final distortion. Note that behavior models consider the variabilities of both the bulk RS field and the geometry of the blanks. Besides, the RS induced by cutting can also be integrated.

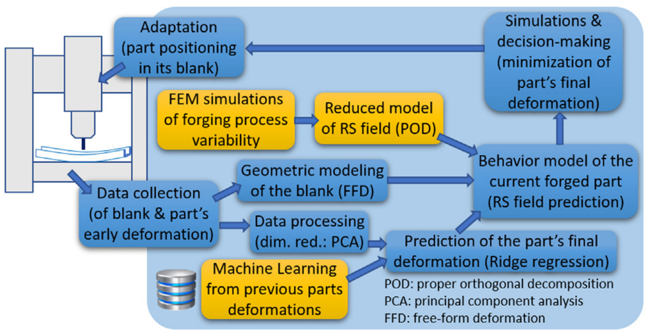

Fig. 1. Hybrid digital twin of forged part, through bulk residual stress (RS) field, to reduce distortion in machining (online modules in bleu and offline ones in yellow).

The approach is generic, applicable for parts with basic geometry (like rolled plate) as well as more complex geometries. It is particularly interesting for long parts (where simulations can be simplified to 2D FEM). The proposed hybrid digital twin of forged part is individualized (for each part), of high-fidelity (of behavior), near real-time (for rapid decision) and controllable (with a closed loop); four expected properties of a DT.

3. Presentation of the components of the hybrid DT

3.1. Reduced model of forging process variability

The main issue that is addressed in this paper, is the variability of the bulk RS field. In order to model some realistic shapes of bulk RS fields, physic-based simulations are suitable. Thermo-mechanical FEM simulations of the forging process variability are thus proposed. But computation times are incompatible with near real-time application. Reduced models of FEM simulation of the bulk RS field variability are thus proposed for the hybrid digital twin of forged part. The method used here is a proper orthogonal decomposition (POD). Several FEM simulations are performed, considering potential defects and gaps, compared to a nominal case. For forged parts, it can be variability of process parameters, such as water temperature for quenching. The RS field extracted from the mesh elements for each simulation, form vectors that are then concatenated in a global matrix $\mathbf{M}$, of size n $\times$ p with n the mesh size and p the number of simulations (snapshots). Then, singular value decomposition (SVD) was chosen to perform the decomposition $\mathbf{M} = \mathbf{U}\Sigma\mathbf{V}$, with Σ the matrix of singular values, $\mathbf{U}$ and $\mathbf{V}$ the matrices of right and left eigen vectors. The columns of $\mathbf{U}$ represents the principal modes of variability of the RS field. A reduced model, of lower order r (r < p), is then deduced. It is a linear combination of the r modes corresponding to the most energetic eigenvalues:

$$\boldsymbol{S_r} = \sum_{i=0}^{r} a_i \mathbf{u_i} = \mathbf{U_r} \cdot \boldsymbol{a} \tag{1}$$

with $\mathbf{U_r}$, of size n $\times$ r, the modal basis of the first r modes and $\boldsymbol{a}$ the vector of r coefficients a_i that control the behavior model, through the bulk RS field $\boldsymbol{S_r}$ of each forged part.

In the case of long parts, a simplification of the 3D FEM to 2D FEM simulations is interesting, to reduce the computation cost of the model reduction construction. In that case, multiple cross-sections can be defined along the part and the global distortion of the part is integrated from the curvatures induced in each of the sections (C). Curvatures Γ can be easily computed by the beam theory, $\mathrm{EI_{Gz}}\Gamma = M_z$ (with E the Young modulus and $\mathrm{I_{Gz}}$ the second moment of area), where the moment of flexion M_z results from the longitudinal residual stress $\boldsymbol{S_r}$ in section C and the moment arm z:

$$M_z = \iint_c z\boldsymbol{S_r}(y,z)dS \tag{2}$$

3.2. Prediction of the final deformation

As described in Section 2, in-process measurements are necessary to capture the specific behavior of each part during machining. $\mathrm{E_0}$, $\mathrm{E_e}$, $\mathrm{E_f}$ define respectively the initial state of the parts before any machining (the blank), the early state after a first rough machining step and at the final state after machining. Since the adaptation of the machining process must be determined at an early stage $\mathrm{E_e}$, the geometry of the blank and the early deformation at $\mathrm{E_e}$ can be used to predict the final deformation at $\mathrm{E_f}$, which can be used to reduce and optimize the machining process, through a behavior model of each part.

Capturing the geometry and the deformation of large parts requires a large number of points (e.g. by probings on a machine-tool or with a 3D scanner). Besides measures are done at multiple steps of the machining. However, data collection in industrial environment is difficult and only a limited number of parts can be available for measurement and then training of the models, due to the production rates notably. Such industrial datasets face the "curse of dimensionality", with too few observations (the parts) compared to the number of variables (the measures), and a dimension reduction should be performed. A principal component analysis (PCA) is thus proposed to reduce the dimension of the dataset of deformation measurements (probed at E_0, E_e, E_f). The values of the first PCA components at E_0 and E_e of the training datasets, and their interactions, are then used as input $\boldsymbol{X}$ of a regression model to predict the final deformations (E_f), through its first PCA component noted $\boldsymbol{Y}$. As predictive model, a Ridge regression was chosen. It is a linear regression with L2-norm regularization (by μ) on its coefficients $\boldsymbol{m}$ during their training.

$$\min_{\boldsymbol{m}} (\boldsymbol{Y} - \boldsymbol{mX})^2 + \mu \parallel \boldsymbol{m} \parallel^2 \tag{3}$$

3.3. *Behavior model of the current part*

a) *Geometric model*

Because of the heterogeneity in the bulk RS field, the positioning of the machined part in the blank is important. However, the mesh of the RS field model (built with the POD) relies on a nominal geometry of the blank that should be adapted to comply with the real curvature and thickness of each blank. This adaptation is done with a morphing technique, called free form deformation (FFD). The mesh encapsulated in the FFD box is deformed by interpolating the displacements of the control points of FFD model.

In this way, a simplified geometrical model of each part is obtained by morphing the part's nominal mesh. It is then used to build the geometrical model of the part at each machining step, by Boolean operations in relation to the material removal. The deformation induced by the bulk RS field at each machining steps can hence be computed for each part. In the case of a long part, the problem can be simplified in 2D, with cross-sections geometries (cf. Fig. 2) adapted to each part by morphing.

b) *Identification of behavior model*

The bulk RS field of each part is estimated through an optimization problem (Eq. (4)), at an early stage in machining. The objective is to find a RS field ($\boldsymbol{S_r}$), close to a nominal field ($\boldsymbol{S_n}$) and compatible with the early measures (me, at E_e) and prediction (pr, at E_f) of deformation of the part at each machining steps (through curvatures Γ). $\Gamma^{\mathrm{Ef,pr}}$ derives from $\boldsymbol{Y}$ in Eq. (3). The first constraint ensures the equilibrium of the RS field in the blank.

$$\begin{aligned}
&\textit{minimize}_{\boldsymbol{a}} && (\boldsymbol{S_r}(\boldsymbol{a}) - \boldsymbol{S_n})^2 \\
&\textit{subject to} && \left| \Gamma^{E_0}_{y,z}(\boldsymbol{a}) \right| < \varepsilon \\
& && (1-\rho)\Gamma^{\mathrm{E_e,me}} < \Gamma^{\mathrm{E_e}}_{y,z}(\boldsymbol{a}) < (1+\rho)\Gamma^{\mathrm{E_e,me}} \\
& && (1-\rho)\Gamma^{\mathrm{E_f,pr}} < \Gamma^{\mathrm{E_f}}_{y,z}(\boldsymbol{a}) < (1+\rho)\Gamma^{\mathrm{E_f,pr}} \\
& && \mathbf{a}_{min} < \boldsymbol{a} < \mathbf{a}_{max}
\end{aligned} \tag{4}$$

In this way, the behavior model of each part relies on the coefficients $\boldsymbol{a}$ (cf. Eq. (1)) that control the reduced model of RS field $\boldsymbol{S_r}$. ρ and ε are error tolerances for the optimization. $\mathbf{a_{min\text{-}max}}$ boundaries result from the $\boldsymbol{a}$ parameters of the training dataset. Both vertical (z) and horizontal (y) part distortions are considered.

c) *Adaptation of the machining*

Once the bulk RS field of the part being machined estimated at an early stage E_e, the final deformation can be simulated more accurately than with the nominal RS field. The behavior model of the part enables the simulations of different adaptive solutions to reduce the final distortion of the part after machining. In a first approach in this paper, the positioning of the part in its blank was chosen as optimization.

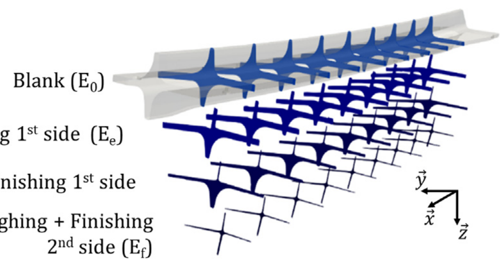

Fig. 2. Geometric model of the cruciform, at each machining step.

Since enough uncut material remains at an early stage of machining (E_e), the positioning of the part in its blank can still be optimized. To find the optimal position, a Genetic Algorithm is used. The algorithm translates and rotates the mesh corresponding to the final part in the predicted RS field and computes the displacements induced by the interpolated RS field. Positions that are found to be outside of the remaining material are penalized to ensure the feasibility of the proposed optimal solution. Finally, the optimized coordinate system of the part is sent to the CNC machine.

4. Industrial use-case

4.1. *Cruciform forged part*

The use case of the study is a cruciform of aeronautic structure that is machined in a long forged blank of aluminum alloy. The blank (gray solid in Fig. 2) is about 6 m long and 1 m width. The thickness is about 5 cm, and one-third on the final part. After machining, the range of variation of the part distortions is a few centimeters, which is problematic.

From each blank (E_0), one part is machined in three steps (including E_e and E_f). The evolution of the part geometry along the machining process is illustrated in Fig. 2, for several cross-sections in bleu. The deformations of 19 cruciform parts were measured (at E_0, E_e and E_f); by probing 100 points on the machine-tool (during about ten minutes), after unclamping of the part.

4.2. *Digital twin of cruciform forged part*

The objective of the hybrid digital twin of forged part is to manage the variability of the bulk RS field, in order to reduce the post-machining part distortion.

Several hypotheses can be made in relation to the geometry of the cruciform forged part. Due to the thickness of the final part, the RS induced by the cut can be neglected. Besides, it is assumed that the bulk RS field can vary along the part, with potentially different field shapes and magnitudes. Lastly, due to the length of the cruciform (compared to the width), 3D FEM simulations can be simplified in 2D FEM simulations of the forging process variability in the cross-sections of the part, associated to the beam theory to assess the part distortion (cf. Section 3.1).

Concerning the forging process variability, before quenching, the cruciform parts undergo a solution heat treatment, in order to relieve the residual stress induced by forging. The RS field is thus assumed free after this homogenization, and the simulation of the forging steps is useless. Only the quench and the cold compression coming after are then considered. Their 2D FEM thermo-mechanical simulations were then computed, in Abaqus software, for seven potential defects or deviations of key process parameters of the quenching and cold compression of the cruciform (such as quenching temperature or die positioning errors), cf. [13].

Concerning the predictions of part deformation, as explained in 3.2, machine learning from the previous parts deformations is suitable. However, the dataset is composed of hundreds of variables (probings) for only 19 observations (cruciform parts), which presents a data dimension issue. To solve it, a dimension reduction by PCA is performed on the dataset and the part deformation is hence depicted

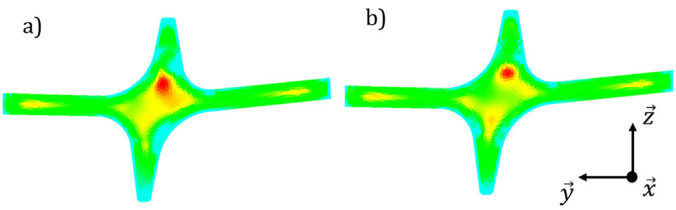

Fig. 3. Reduced model of bulk RS field: (a) nominal RS field S_n and (b) RS field prediction S_r for a specific part, at an early stage of machining; with different RS field shapes, with traction (in yellow and red) in the core of the blank, and compression (in blue and green) close to the skin.

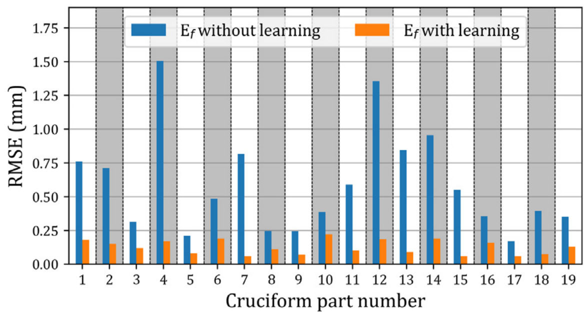

Fig. 4. Prediction of final part deformation, with/without machine learning from the previous parts deformations.

by one variable: the first component of PCA. The Ridge regressive model is then trained with the resulting deformation at E_0 and E_e to predict the deformation at E_f.

In this way, for each new cruciform, the behavior model (i.e. coefficients $\boldsymbol{a}$ of the reduced model of the bulk RS field) is identified at an early stage of machining (E_e), in relation to Eq. (4): from the measures of the part's early deformation ($\Gamma_{y,z}^{E_e}$) and the predictions of final deformation ($\Gamma_{y,z}^{E_f}$ by machine learning).

Due to the small dataset, the hybrid approach was evaluated by leave-one-out: iteratively, one part is selected to test the model, and the 18 other ones are used for the training of the Ridge regression model, before this evaluation.

Fig. 4 shows the root mean squared error (RMSE) computed for the test part, between its final distortion estimated by the behavior model (at the early stage of rough machining E_e) and its final measurements (E_f) by probing. Results are compared with and without machine learning from the previous parts deformations (i.e. with/without considering $\Gamma_{y,z}^{E_f}$ in Eq. (4)). It proves that considering the prior parts deformations leads to better estimations of the bulk RS field. Indeed, the average RSME error (computed over the 19 parts) drops from 0.59 mm without (Fig. 4. in bleu), to 0.13 mm with machine learning of previous deformations (in orange). Therefore, the machine learning and physic-based simulations of RS field are necessary to tackle the variability and enable accurate predictions with the behavior model.

Since the behavior model is of good fidelity and identified at an early stage of machining, it enabled simulations of adaptive solutions in order to reduce the part distortion after machining. In this paper, the part positioning in its blank is optimized, but other solutions

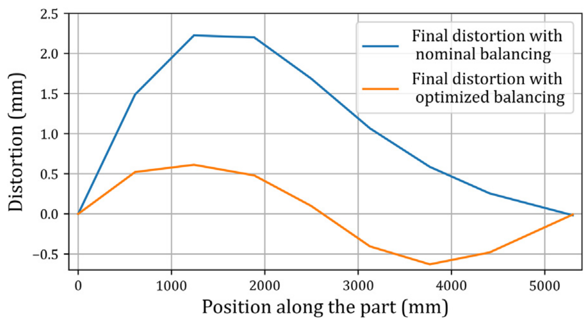

Fig. 5. Reduction of final part distortion between nominal and optimized positioning in the blank, obtained by the DT behavior model.

exist. As suggested in Section 3.3, a Genetic Algorithm (GA) is then applied to perform simulations of different positionings with the behavior model of each part, once the bulk RS field identified. This optimization takes less than a second. Fig. 5 illustrates the distortion for cruciform n°4 as an example of result. It shows the final distortion of the part for a nominal positioning (as it would be machined without closed loop to machine-tool) and the optimal one (resulting from RS model and GA). Here shifting the part in the blank of 4.1 mm and 5.2 mm in the *y* and *z* directions (cf. Fig. 3 coordinate system) reduces the final maximal distortion from 2.4 mm to 0.6 mm.

5. Conclusion

Machining large parts from forged blanks is challenging due to the variability of the bulk RS field (since both magnitude and shape vary). To tackle this difficulty issue, a hybrid digital twin was proposed. The behavior model relies on a reduced FEM model of bulk RS field variability, in-situ measurement and machine learning from previous parts distortions. Without one of the three elements, it would not be possible to predict accurately the RS field; as demonstrated for machine learning without which the behavior model would be inaccurate.

The aeronautic use-case has shown that, despite the complex geometry and variability of the RS field shape, the proposed hybrid digital twin for forged part leads to accurate prediction of RS field, early in the machining, enabling a reduction of the part's final distortion.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors acknowledge the partial funding by French ANRT of the CIFRE PhD with Airbus.

References

[1] Li JG, Wang SQ (2017) Distortion Caused by Residual Stresses in Machining Aeronautical Aluminum Alloy Parts: Recent Advances. *International Journal of Advanced Manufacturing Technology* 89:997–1012. /1.
[2] Louhichi M, Poulachon G, Lorong P, Outeiro J, Monteiro E (2022) Experimental and Simulative Determination of Residual Stress during Heat Treatment of 7075-T6 Aluminum. *Procedia CIRP* 108:82–87.
[3] Akhtar W, Lazoglu I, Liang SY (2022) Prediction and Control of Residual Stress-Based Distortions in the Machining of Aerospace Parts: A Review. *Journal of Manufacturing Processes* 76:106–122.
[4] Hussain A, Lazoglu I (2019) Distortion in Milling of Structural Parts. *CIRP Annals* 68:105–108. /1.
[5] Madariaga A, Arrazola PJ, Perez I, Sanchez R, Ruiz JJ, Rubio FJ (2018) Reduction of Distortion of Large Aluminium Parts by Controlling Machining-Induced Residual Stresses. *International Journal of Advanced Manufacturing Technology* 97:967–978.
[6] Yang Y, Yang M, Li K, Li R (2014) Comparison and Analysis of Main Effect Elements of Machining Distortion for Aluminum Alloy and Titanium Alloy Aircraft Monolithic Component. *International Journal of Advanced Manufacturing Technology* 70:1803–1811. /9.
[7] Cerutti X, Mocellin K, Hassini S, Blaysat B, Duc E (2017) Methodology for Aluminium Part Machining Quality Improvement Considering Mechanical Properties and Process Conditions. *CIRP Journal of Manufacturing Science and Technology* 18:18–38.
[8] Guiassa J, Mayer R (2011) Predictive Compliance Based Model for Compensation in Multi-Pass Milling by On-Machine Probing. *CIRP Annals* 60:391–394. /1.
[9] Hao X, Li Y, Li M, Liu C (2019) A Part Deformation Control Method Via Active Pre-Deformation Based on Online Monitoring Data. *International Journal of Advanced Manufacturing Technology* 104:2681-2692.. /5.
[10] Liu M, Fang S, Dong H, Xu C (2021) Review of Digital Twin about Concepts, Technologies, and Industrial Applications. *Journal of Manufacturing Systems* 58:346–361. /B.
[11] Zhao Z, Li Y, Liu C, Gao J (2020) On-Line Part Deformation Prediction Based on Deep Learning. *Journal of Intelligent Manufacturing* 31:561-574.. /3.
[12] Llanos I, Lanzagorta JL, Beristain A (2017) Part Distortion Modeling on Aluminum Slender Structural Components for Aeronautical Industry. *Procedia CIRP* 58:158-162.
[13] Chabeauti H, Ritou M, Lavisse B, Germain G, Charbonnie V (2022) Numerical Investigation and Modeling of Residual Stress Field Variability Impacting the Machining Deformations of Forged Part. *Procedia CIRP* 108:687–692.